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Sociometric Indicators of Leadership: An Exploratory Analysis

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**U.S. Army Research Institute
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SOCIOMETRIC INDICATORS OF LEADERSHIP: AN EXPLORATORY ANALYSIS

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Introduction

Effective interpersonal interaction is a critical task for all Army leaders. The success of a mission often depends on leaders being able to communicate, and followers being able to understand, the requirements of the mission. Traditional research and assessment methods focusing on leader and follower interactions require direct observation—a challenging and time-consuming approach. Sociometric badges may provide a technological solution allowing for detailed analysis of the real-world communication patterns arising between leaders and followers. Sociometric data would help Army instructors and evaluators supplement and streamline existing observational protocols and assessment methods. This research provides an initial test of sociometric badges in the context of the U.S. Army's Officer Candidate School (OCS) to evaluate the usefulness of this technology for providing data to support leader assessment and development. Although the technology is promising, some modifications will be required for seamless and effective implementation in an Army field setting.

The Context of Army Leader Development

The U.S. Army Operating Concept stresses the challenges of thriving and succeeding in a complex world (U.S. Department of the Army, 2014c). Given this complexity, the Army is increasingly emphasizing broad training objectives across cognitive, social, and physical dimensions, with the objective of optimizing the performance of each Soldier through Soldier-centered instruction (e.g., U.S. Department of the Army, 2014b; U.S. Department of the Army, 2011). Consistent with this emphasis, the Army leadership requirements model (U.S. Department of the Army, 2012) addresses wide-ranging requirements across various leader attributes and competencies including character, presence, intellect, leads, develops, and achieves (see Figure 1). While this broadening emphasis is positive given the necessities of the operational environment, there is an emerging need to address how best to train and assess Soldiers across all of these dimensions.

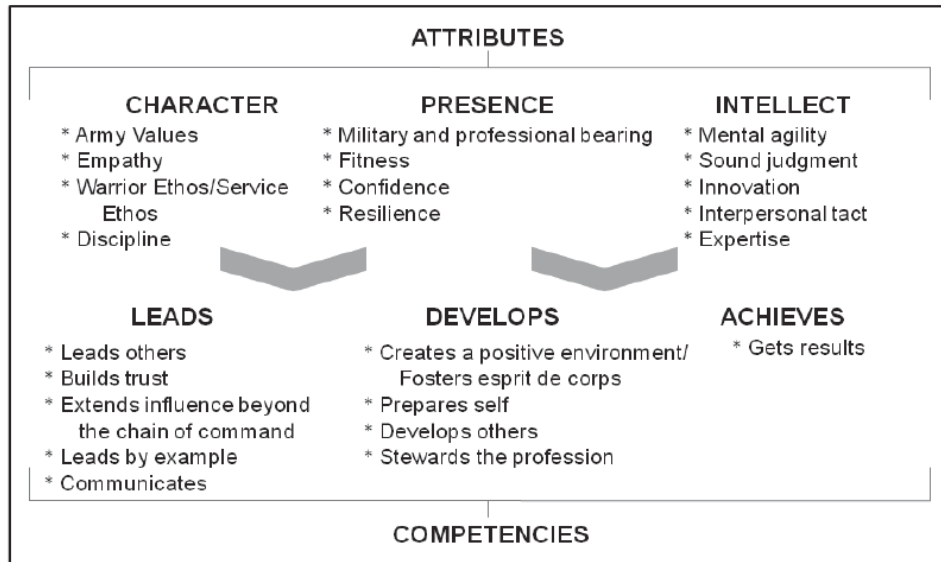


Figure 1. Army leadership requirements model.

The mission of OCS, for instance, is to provide “trained, agile, and adaptive junior Officers for an Army at war who are ready today and relevant for tomorrow’s challenges” (U.S. Department of the Army, 2014a, p. 6). Currently in OCS, Army leadership attributes and competencies are typically graded on Likert-type scales with four levels: needs improvement, satisfactory, excellent, and outstanding based on a brief description of each attribute or competency. OCS cadre use this scale in a paper and pencil leadership assessment tool to evaluate candidates across all the attributes and competencies in the leader requirements model (Figure 1).

In total, there are approximately 30 items to be rated each time a candidate is observed in a leadership role. This large assessment burden, when combined with a high instructional load and difficult candidate to cadre ratios, challenges instructors in terms of their ability to accurately capture candidate growth and performance. The problem is two-sided: increased assessment requirements limit the time available for instruction, but, limiting the time for assessments may affect the accuracy of the evaluations. Moreover, given the reliance on observer/cadre-based assessments, lingering issues remain including the potential for inconsistency stemming from rater bias, and a limited ability to capture the true nature of the candidates when instructors are not present and candidates are not being observed (i.e., the Spotlight Ranger problem).

There is a requirement, therefore, to make assessment less cumbersome, more consistent, continuous, and actionable while capturing the full range of attributes and competencies that are necessary for exercising effective leadership in a complex world. This research explored whether and how wearable sensors can be used to assess leader and follower communication patterns, presenting a case study to illustrate the technology while exploring its future applications. Based on this initial investigation, recommendations for sensor development and future research that will enable full exploration of this approach are discussed.

Relational Nature of Leadership

Leadership is a complex social phenomenon (Fallesen, Keller-Glaze, & Curnow, 2011). The Army clearly recognizes both the complexity and social nature of leadership, as can be seen in the comprehensive delineation of leader attributes and competencies in ADRP 6-22 (U.S. Department of the Army, 2012) and the emphasis on items such as building trust, empathy, and communication.

The social and relational nature of leadership has been studied in the context of social exchange theory (SET; see Cropanzano & Mitchell, 2005), which posits that the mutual reciprocity of effort characterizes the quality of the relationship between individuals. Leader-member exchange (LMX), a corollary of SET, is one of the most widely studied leadership theories. LMX helps explain the process by which the quality of the relationship between a leader and follower impacts various individual, team, and organizational outcomes (Martin, Guillaume, Thomas, Lee, & Epitropaki, 2016). LMX theory was originally introduced as the vertical dyad linkage approach to leadership by Dansereau, Graen, and Haga (1975) who argued that (a) not all work group members are treated the same by the leader; (b) these differences in treatment can influence leader-member relationships; and (c) leadership research should focus on the relationship between a superior and individual subordinate rather than on the work group.

According to LMX theory, leaders may vary the resources they channel into their relationship with each of their subordinates. Within LMX, high-quality relationships are characterized by each individual taking continuous action to produce mutually beneficial outcomes (Cropanzano, Prehar, & Chen, 2002). In a meta-analysis examining LMX and performance, researchers found that LMX ratings were positively related to task performance and citizenship behaviors, and negatively related to counter-productive behaviors (Martin et al., 2016). For example, subordinates who perceive their leader to be supportive may put in extra effort on the job. Conversely, poor-quality LMX relationships have been shown to predict retaliatory behaviors among subordinates (Townsend, Phillips, & Elkins, 2000).

One approach to examining the social and relational nature of leadership is through the use of network analytics (Carter, DeChurch, Braun, & Contractor, 2015). Network analytics have been used to examine leadership within a variety of social network frameworks, including friendship, respect, trust, influence, power, and perception. These networks can be viewed from an individual perspective, which describes the power of an individual's position within a social network, or they can be viewed from a broader, aggregate focus, which examines the structure of the network such as its density and centralization (Carter et al., 2015). For example, these techniques have been used to show that leaders who trust their employees are, in turn, trusted by their employees (Lau & Liden, 2008). Further, network analytics have been used to examine other organizational variables such as group or team performance (Balkundi & Harrison, 2006; Carson, Tesluk, & Marrone, 2007; Mehra, Dixon, Brass, & Robertson, 2006), group effectiveness (Oh, Chung, & Labianca, 2004), team climate strength (Zohar & Tenne-Gazit, 2008), and person-organization fit (Anderson, Spataro, & Flynn, 2008).

Social networks have been examined using self-report surveys, peer ratings, and behavioral coding. Self-report surveys and peer ratings typically assess the participants' view of others in relation to their status, influence, or other social ties (Carter et al., 2015). Behavioral coding involves having raters view and code actions of individuals that relate to leadership or power relations. Coding may be done in person or through viewing recordings (Aime, Humphrey, DeRue, & Paul, 2014). There are limitations regarding the use of self-reports to examine social networks (Shaughnessy, Zechmeister, & Zechmeister, 2012). One concern is that participants may either be deliberately misleading or report inaccurate information due to memory failures, affecting accuracy. Another concern is that self-reports are subject to bias from socially desirable responding. Though behavioral coding may eliminate some of the biases of self-report, it can be very time-consuming, both in terms of the coding itself and in terms of assessing the reliability and validity of that coding. Wearable sensors offer an alternative to the current methods of examining social network ties.

Sociometric Approaches to Leadership Assessment

Given the complex social nature of leadership development and performance, methods that provide reliable, unbiased measurements and enable continuous collection of interactions in a manner that does not put undue burden on instructors would be useful. Wearable sensors offer a potential approach. One such tool, the sociometric badge (see Figure 2), was developed by Olguín Olguín and Pentland (2008) to automatically collect behavior related to social interactions. The badges contain multiple sensors allowing for the simultaneous collection of

multiple kinds of data. The microphone collects compressed data, which allow for analysis of speech without the content of the conversation, to maintain privacy. This includes conversational back-and-forth, as well as pitch, tone, and amplitude of speech. The accelerometer detects movement. The infrared sensors on the badges detect face-to-face interactions within a distance of approximately 8 feet and an angle of ± 15 degrees. These thresholds help to reasonably ensure that only significant interactions between individuals are recorded. The Bluetooth sensors measure proximity within a larger radius of approximately 20-30 feet and help to identify interactions that may not be face-to-face. For each of these sensors, a *ping* is recorded and timestamped on the badges when a detection between badges is made. These pings can be grouped into temporally contiguous clusters, which represent a conversation or interaction between individuals.

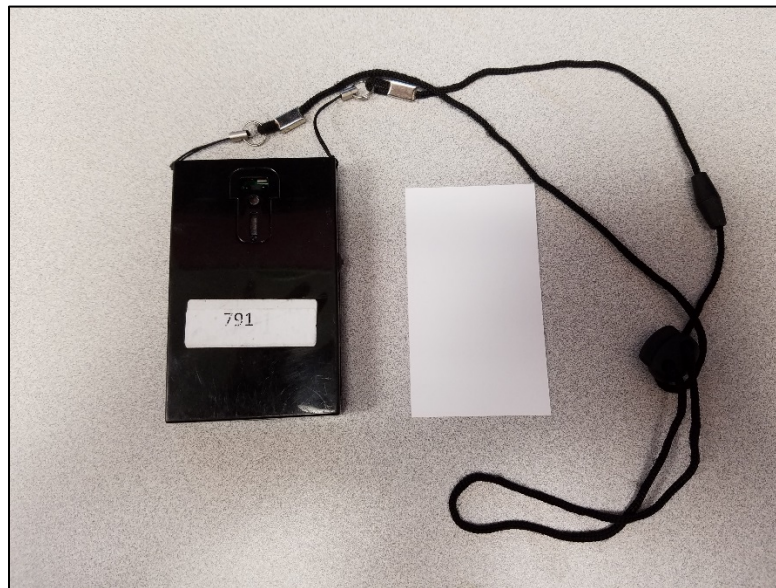


Figure 2. Sociometric badge.

Sociometric measures, or non-verbal measures of social interactions, have the potential to complement research on the relational aspects of leadership; that is, how the dynamics of interpersonal relationships impact leadership (Uhl-Bien, 2006). Sociometrics have been hailed as objective and difficult to manipulate, and therefore less prone to bias than traditional measures such as self-report surveys (Olguín Olguín & Pentland, 2008). Wearable sensors such as accelerometers, infrared and Bluetooth sensors, and microphones enable automated capture of behavioral characteristics such as tone and volume of speech, as well as body position, proximity, and face-to-face interactions. These data are then converted to sociometrics that can provide information about social interactions, e.g., who is talking to whom, and how often they are interacting (e.g., Olguín Olguín & Pentland, 2008).

Sociometric measures have been used in a variety of contexts. For example, Jones, Lansey, and Diedrich (2012) examined interpersonal interactions among members of two submarine crews using sociometric badges. They suggest that volume data are useful indicators of tension and can help differentiate teams based on experience. The authors also found that infrared data could be used to examine with whom and which workstations crew members interacted. These types of data could be used to examine team and leader processes. Kim,

Chang, Holland, and Pentland (2008) used sociometric data to provide real time feedback on group collaboration. Dominant and non-dominant group members were identified based on sociometric data, and real-time visual feedback was provided. This feedback allowed participants to see how balanced and interactive group collaboration was. This study demonstrated that sociometric data could be used in real-time to provide feedback that influences behavior. Finally, Duchon et al. (2014) examined the use of sociometrics in the context of mission command. These researchers used sociometric badges and other data, such as e-mail, to create a database of communication data. These data were used by observers/coaches/trainers during a mission command exercise to assess unit performance.

A case study was conducted to explore the potential use of sociometric data in assessing leadership. Data were collected from Officer candidates during a field exercise and examined for patterns of interactions to determine the feasibility of sociometric measures in this context.

Method

Participants

Thirty candidates from one class at OCS participated in this case study. The majority of Officer candidates were male (73%; 23 out of 30) and 23% (7 out of 30) had prior military service. All Officer candidates had four-year college degrees.

Procedure

Sociometric badges were worn by the candidates during a squad-level field exercise. The candidates were briefed on the purpose of the study and given an informed consent form to read and sign. Candidates were briefed on their rights as participants in research, including their right to choose not to participate at any time without penalty. Those candidates who chose to participate were assigned a sociometric badge to wear during the observed training period. Occasionally, especially in the field environment, badges broke. When this happened, candidates were provided a replacement badge.

Data collection focused on the behavior of two squads where the candidates were given missions to accomplish with their squad of 8-10 candidates. Candidates were rotated into different leadership positions, including Squad Leader (SL), and Alpha (ATL) and Bravo Team Leaders (BTL). Candidates were graded on their performance as SL by the OCS Cadre. For each lane in this exercise, candidates planned and executed a mission employing Troop Leading Procedures, and the missions involved movement, reconnaissance, and enemy contact. The candidate SL was given a mission brief by the OCS cadre, for example, movement to contact or squad attack. SLs were required to plan the mission, issue an order to the squad and begin movement. While moving to their objective, the squad would encounter the enemy and be exposed to small arms or indirect fire. Maintaining command and control, the squad leader had to assess the situation and tactically maneuver their squad to accomplish their assigned mission. Once a lane was complete, the cadre conducted an after action review with the squad.

Analyses

Infrared and Bluetooth signal pings from the sociometric badges were analyzed. As previously discussed, the infrared sensors on the badges detect face-to-face interactions at close ranges whereas the Bluetooth sensors measure proximity within a larger radius to identify interactions that may not be face-to-face (e.g., face-to-back or back-to-back). For each of these sensors, a ping is recorded and timestamped on the badges when a detection between badges is made.

Following collection, data were downloaded from the badges and stored in an SQL database. The first step in processing the data was to cluster the infrared and Bluetooth pings. Individual pings may be recorded in situations where no real interactions between individuals were occurring, such as passing each other quickly or briefly stepping into Bluetooth detection distance. To filter out these errant data points, groups of pings in the data occurring within a reasonable temporal proximity of each other (in this case, a threshold of 60 seconds) were identified. This step clustered each of the signals into “conversations,” or groups of pings that likely provide reasonable evidence of a true interaction between individuals. Based on these data, a social network for each exercise was built and visualized. The lines on the social network visualization indicate interactions, thicker lines indicate more interactions than thinner lines. An interaction dominance score was calculated for each squad leader to determine the overall level of involvement of the leader with his/her subordinates. This score was defined as the ratio of interactions involving the leader to the total number of interactions.

Results

For the two missions that were analyzed, the total number of interactions recorded (across both Bluetooth and infrared) were small (53 and 69 total interactions on the two missions). Of the 53 total recorded interactions for Mission 1 (see Figure 3), only six involved the SL. Five of those six were with the ATL and the other interaction was with a member of Alpha team. No interactions were recorded between the SL and the BTL. For this mission, the leader’s dominance score was 0.113 (i.e., the leader was involved in only 11.3% of the interactions). The low dominance score was accompanied by a relatively high degree of interaction between the ATL and BTL (13 [24.5%] total interactions). A detailed description of the number of interactions can be found in Table 1.

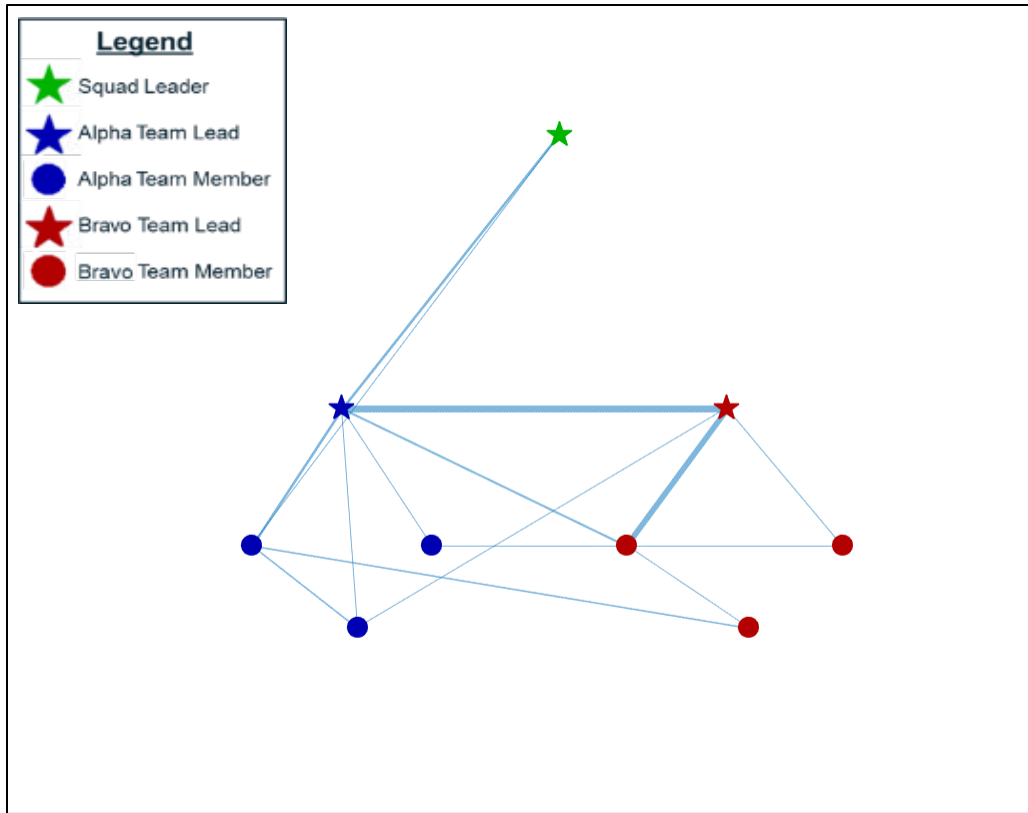


Figure 3. Mission 1 social network.

Table 1
Interactions by Squad Member

	SL	ATL	ATM 1	ATM 2	ATM 3	BTL	BTM 1	BTM 2	BTM 3
SL	--	5	1	0	0	0	0	0	0
ATL	12	--	5	1	1	13	4	0	0
ATM 1	0	0	--	3	0	0	0	0	3
ATM 2	6	0	0	--	0	1	0	0	0
ATM 3	8	4	0	0	--	0	0	2	0
BTL	10	4	0	0	4	--	11	2	0
BTM 1	0	0	0	0	0	3	--	0	1
BTM 2	0	0	0	1	2	5	0	--	0
BTM 3	1	0	0	0	0	0	0	0	--
BTM 4	1	0	0	0	0	4	2	2	0

Note: Mission 1 interactions are above the diagonal and Mission 2 interactions are below the diagonal. *SL* = squad leader, *ATL* = Alpha team leader, *BTL* = Bravo team leader, *ATM* = Alpha team member, *BTM* = Bravo team member

In contrast, Mission 2 illustrates a drastically different pattern of SL interaction. Of the 69 total interactions occurring during Mission 2, 38 involved the SL (Figure 4). The SL interacted the most with the ATL and BTL (12 and 10 interactions, respectively) and to a lesser degree with other team members. For this mission, the leader's dominance score was 0.551, indicating the SL was involved in 55.1% of the interactions. The BTL had a high degree of interaction with Bravo team members (direct interactions with three out of the four members, 12 total interaction instances with members). The ATL was connected to his/her team by only one direct connection to another team member. The SL had several interactions directly with Alpha team members.

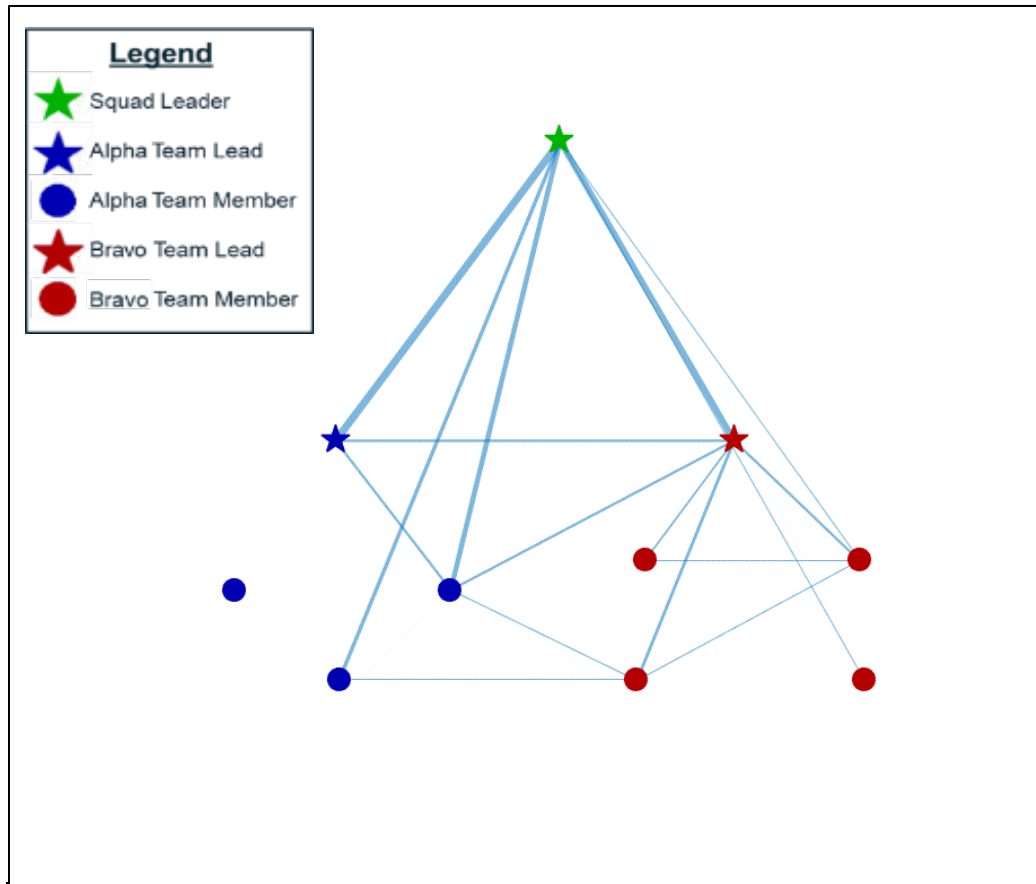


Figure 4. Mission 2 social network.

Discussion

Overall, these results illustrate that the sociometric approach enabled detection of differences in the observed patterns of interaction, suggesting these types of data may be promising for assessing leadership differences in communication styles and interpersonal interactions. Specifically, the results of the sociometric analysis from the first mission indicated that the SL interacted minimally with the TLs and the team members. In this case, a relatively higher degree of interaction was seen between TLs, which may indicate compensation for SL's lack of interaction. In contrast, the results of the second mission show that the SL had a relatively high degree of interaction with the TLs. The BTL had direct connections with team members and there was also high connectivity among the members themselves. The ATL had only one direct

connection to a team member and there were no other connections among the team. The SL may have intervened by directly interacting with Alpha team members thus requiring a lower level of interaction between the ATL and the team or the SL may have intervened to compensate for the lack of communication by the ATL.

One caveat is that these conclusions are subjective interpretations of the data. Currently, it is unclear if one interaction pattern is associated with more effective leadership or better team performance compared to the other. A much larger data set across many different squads is necessary to reliably model behavior and make data-driven inferences about performance. However, this case study yields a sample set of algorithms and preliminary findings that highlight both the potential benefits and limitations of sensor-based methods of social network analysis.

Novel Measures of Leadership

Building on these findings and earlier research, it is apparent that sociometric approaches have the potential to meet some of the core challenges of measuring leadership—the sensors and general approach have been used to measure behavior within organizations, employing methods that are relatively unobtrusive, unbiased, and continuous. These findings indicate that there may be opportunities for novel assessments of leader development. We explore this issue by illustrating hypothetical measures that might be applied in the future.

Focusing on OCS and following the Army leader requirements model (U.S. Department of the Army, 2012), the assessed leadership attributes and competencies are multiple, comprehensive, and in many cases, have the potential to be somewhat subjective in nature. For instance, consider the category presence, the image that a leader projects, and its specific sub-item military and professional bearing, which is defined as projecting a command presence and professional image of authority. Certainly, part of projecting a commanding presence is looking and acting the part in terms of dress and customs. Likewise, projecting a commanding presence is related to appearing in control, calm, and confident (across various sub-items for presence). Many elements of presence could simply be observed by instructors, subordinates, or fellow students who are in the vicinity; however, what, if anything, could be captured by sociometric sensors? One could hypothesize, for instance, that presence is associated with speaking at an appropriate volume, as speaking too softly may convey a lack of confidence and speaking too loudly may indicate a loss of control (e.g., yelling to regain control). Likewise, lower variance of pauses between words may indicate calm and confident rather than confused or uncertain, which may be indicated by stopping and starting. In the case of movement, as detected by the accelerometer, excessive pacing may be indicative of nervousness. As shown in Figure 5, upon combining these three elements – speech volume, communication style, and movement—a “sweet spot” emerges that can be associated with positive military and professional bearing, with some amount of variance allowed based on context (i.e. speaking loudly in a live-fire situation would likely be considered appropriate).

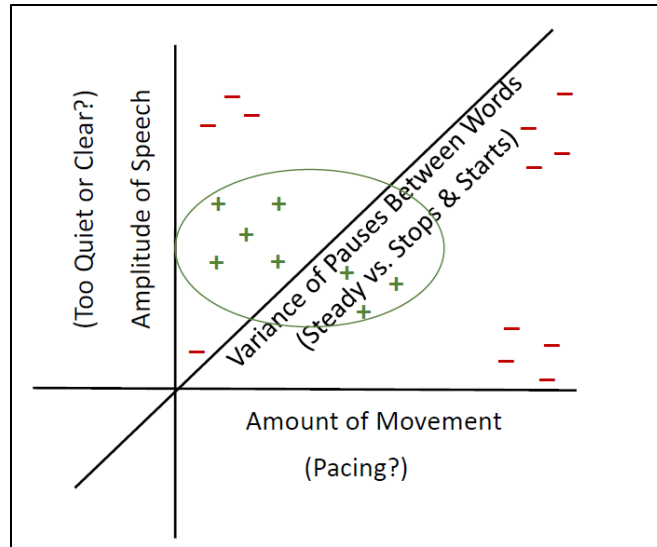


Figure 5. Hypothesized measure of military and professional bearing.

As a second example, consider the Army value *respect*, which is defined as treating others as they should be treated while promoting dignity, consideration, and fairness (see ADRP 6-22). What might be observable via the wearable sensors, and how might this relate to respect? The microphones may capture lack of turn-taking behavior whereas the infrared sensors can detect the extent to which the leader interacts with each of the subordinates. As shown in Figure 6, once again a space is defined by behaviors that correlate with demonstration of respect, allowing for some level of variance based on context.

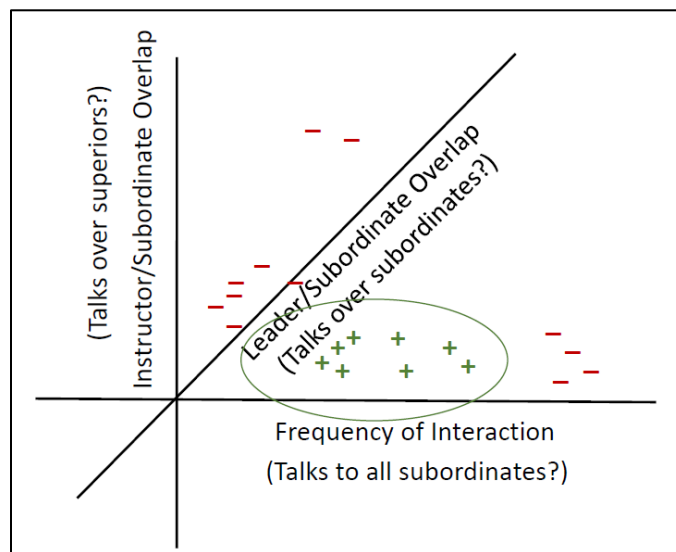


Figure 6. Hypothesized measure of respect.

Findings and Recommendations

Combined, the data and hypothetical future measures illustrate the potential utility of a sensor-based approach to leadership assessment. Using the sociometric badges explored here as an example, it is clear that such wearable sensors can augment instructor observations by enabling measures that are unobtrusive, continuous, repeatable, and objective. At the same time, there are obstacles to be addressed before these tools are truly usable and useful. These obstacles relate to both sensor development and research that must be conducted to guide future application.

Sensor Development. The first key to greater utility concerns the robustness of the sociometric sensors employed in this effort. In the context of OCS, the focus is on learning how to lead a small unit, where many of the graduates will go on to command platoon-sized elements following additional institutional courses. Because of this emphasis, the context of use is shaped by moving and acting in the field. For instance, the squad-sized tasks explored here required moving through the woods in the context of assaulting enemy positions. This meant contending with equipment on the body while running, crawling, or laying prone. The sociometric sensors employed for this effort were not robust enough to withstand the kinetics of the mission, and they were sometimes unable to capture interactions effectively (e.g., sensors were sometimes covered by body armor or badges flipped around). Multiple badges fell apart during testing and had to be replaced. In addition to badges breaking, other badges experienced technical glitches that rendered them unusable, such as needing a new memory card or to sync the internal clock with a computer. Though these issues could typically be addressed fairly quickly in the field by the scientists involved in the efforts, they created delays, increased workload and missing data, and required individuals with the right expertise to be in the field with the candidates. Critical, therefore, is the hardening of the sensors including exploring how they are worn both indoors and in the field to (a) capture genuine interactions in different situations and (b) design sensors to withstand the elements and outdoor terrain, e.g., rain and mud as well as the kinetics of field exercises.

A second area for improvement concerning sensor usability and utility involves time for processing. Though data can be downloaded from multiple badges simultaneously, the process for doing so can be cumbersome and requires numerous physical connections to a hub and substantial time while data processes. In addition, the longer the badges are used, the longer it takes to download data. Adding to the time burden, data must be processed to separate true interactions from erroneous noise. In the long run, availability of data for after action review and instructor feedback must not impose delays between action and review that hamper learning.

Finally, a third area for improvement related to sensor usability and utility concerns how best to enable the capture of interactions. As conceived, the sociometric badges were intended to explore largely face-to-face interactions, for example, around a conference table when in a meeting in an office setting. However, in the context examined here, back-to-face or back-to-back interactions appeared very likely as personnel talked while also maintaining security (e.g. infrared data will not capture interactions when subjects are sitting next to each other, or if one subject is behind the other). While Bluetooth may detect such interactions, it may be very difficult to identify the intended target of communication if groups of Soldiers are closely

spaced. For this reason, one avenue for additional sensor development is to explore sensor suites that are arrayed on both the front and back of participants, and how best to interpret such data. Additionally, the sensors used in the current study may encounter difficulties with detecting field communications, such as hand signals and radio transmissions.

Future Research. Building on the idea that there are a variety of configurations of interactions, a more general area for future research is the continued development of algorithms. Back-to-face communication is one example of a complication of the context explored here. More generally, the issue is the development of algorithms to move concepts from hypothesis to reality for items like those shown above for respect and military bearing. Ultimately, the challenge is to explore algorithm development for a range of items across the categories of leads, develops, achieves, character, presence, and intellect (U.S. Department of the Army, 2012). To do so will require substantial data for development and validation.

Likewise, further research is needed on how best to use mixed methods of assessment across the complete spectrum of Army leader competencies and attributes that organizations such as OCS address. As an example, communication might be ideally suited for assessment via wearable sensors. In contrast, instructors might best be able to assess the Army value integrity. Hence, along with algorithm development, there is additional research that must be conducted on strategies for how to combine sociometric data with other sources, thereby focusing the limited resources of instructors on the key elements that humans must still assess out of the variety of attributes.

Finally, the last area for research concerns how best to use wearable sensors like sociometric badges to provide not only summative assessments but also formative assessments. For instance, it might be interesting to know that a Soldier scores poorly on a final assessment for interpersonal tact or military and professional bearing. Such data might serve to rank Soldiers or point out individual strengths and areas of opportunity. However, little is known about how to take these data and make them actionable to support growth. At one level, this is deceptively simple – for instance, for military and professional bearing, perhaps one could simply give feedback along the lines of “pace less and speak louder.” Yet, such feedback alone focuses only on symptoms and begs the question of how to incorporate such measures into instructional design. The research issue here, yet to be explored, is how and when such data can be used in the context of scaffolding strategies across a variety of direct and indirect instructional approaches.

Conclusions

Wearable sensors offer a potential method for obtaining unobtrusive and objective measures of leadership behaviors. The results of the case study presented in this paper demonstrate that differences in behaviors can clearly be seen in the data from these sensors; however, more groundwork is needed before these devices can be used in realistic training environments or in real time.

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